CHALMERS | GÖTEBORGS UNIVERSITET

VOLVO

COMPLEX PERFORMANCE ANALYSIS OF AUTOENCODER-BASED APPROACHES FOR ANOMALY DETECTION IN DRIVING SCENARIO IMAGES

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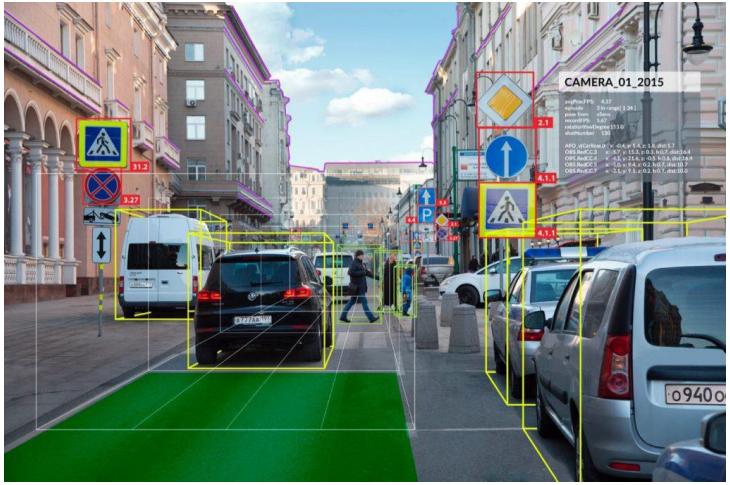
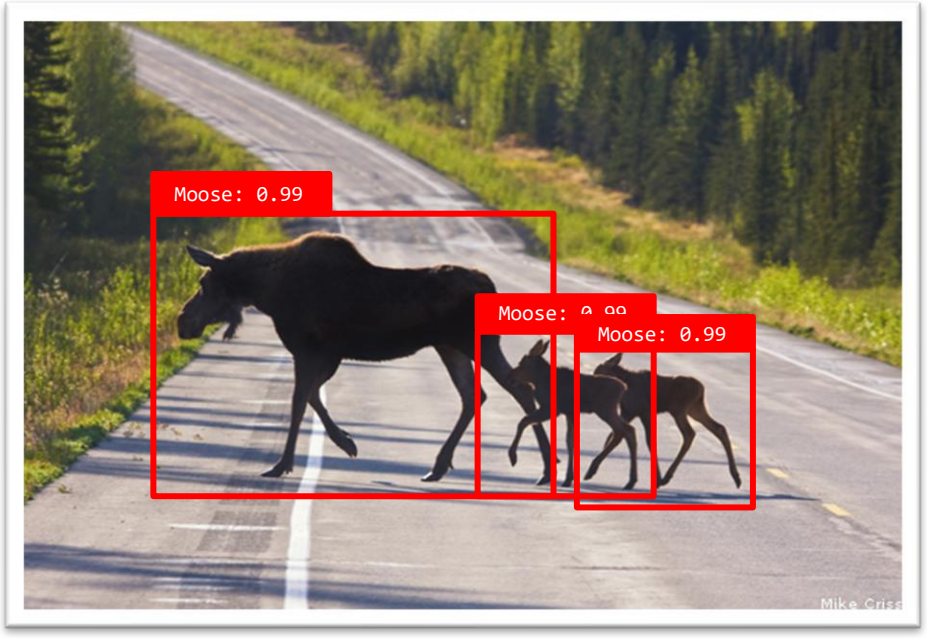
Deep Learning Perception in Automotive

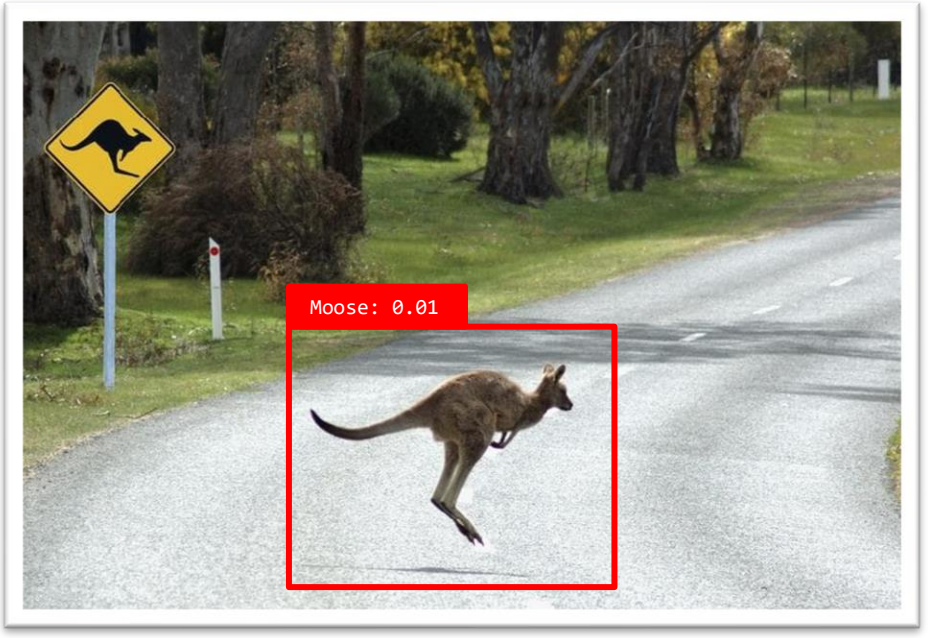
object detection



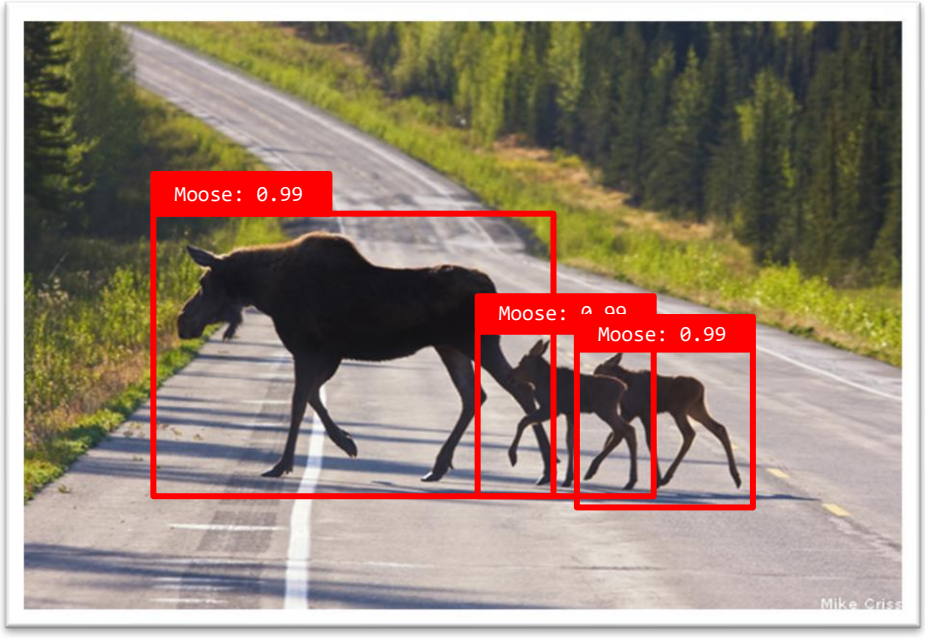
semantic segmentation

Distributional Shift Problem

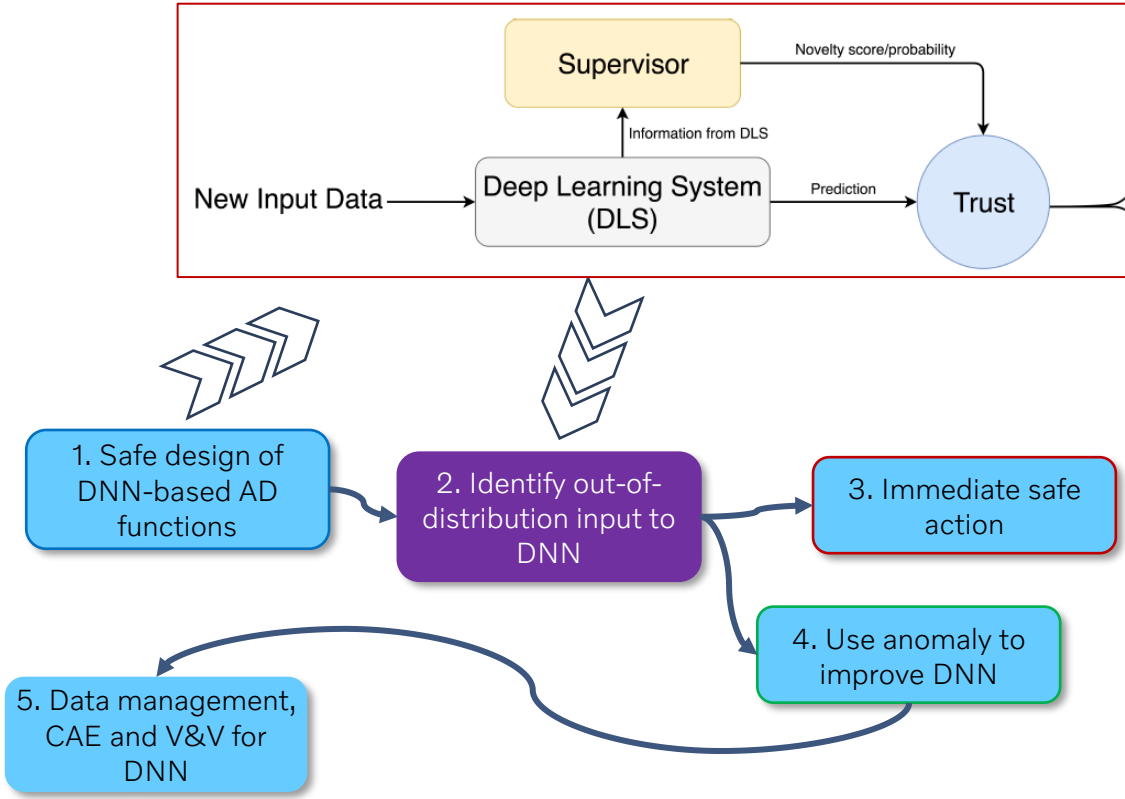




Distributional Shift Problem



“Safety Cage” Architecture

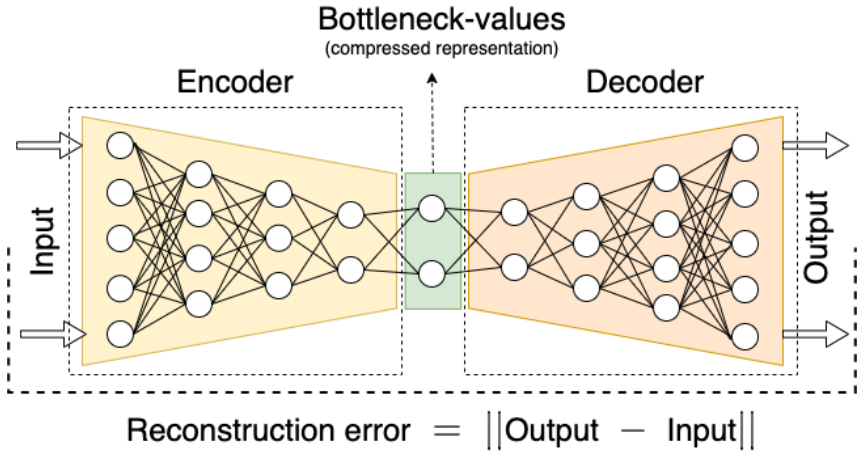


Supervisor (anomaly detection) working principles

- Black-box (data-based, e.g. autoencoders)
- White-box (model-based, e.g. neuron activations)

Autoencoders

Original image



Reconstructed image

Autoencoder-Based Anomaly Detection

Reconstruction error approach

Euclidean distance as anomaly score.

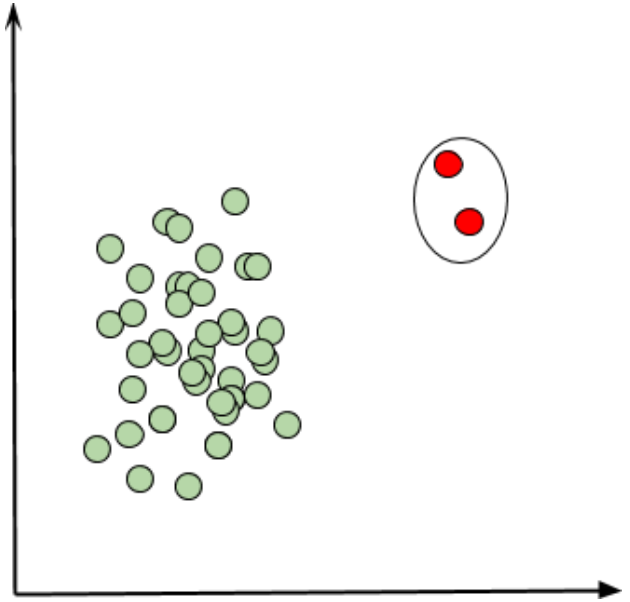
Original image

Reconstructed image

Reconstruction error image

Bottleneck-values approach

LocalOutlierFactor as anomaly score.



Images representations in 2D space

Research Questions

- *RQ1: What is the performance of autoencoder-based approaches for anomaly detection in driving scenario images?*

- *RQ2: What is the robustness of autoencoder-based anomaly detection approaches to color changes in driving scenario images?*

Anomalies in Driving Scenario Images

Context anomalies

Semantic anomalies

Experiments Setup (Data)

- Pro-SiVic generated images
- Empty highway VS highway with cars (cars as anomalies)
- Consider 3 cases: original, modified (changing yellow colors to grey), and greyscale images.
- 256 training images (normal); 100 normal testing images; 31 anomalous testing images.
- Size: 192x320

Normal image

Anomalous image

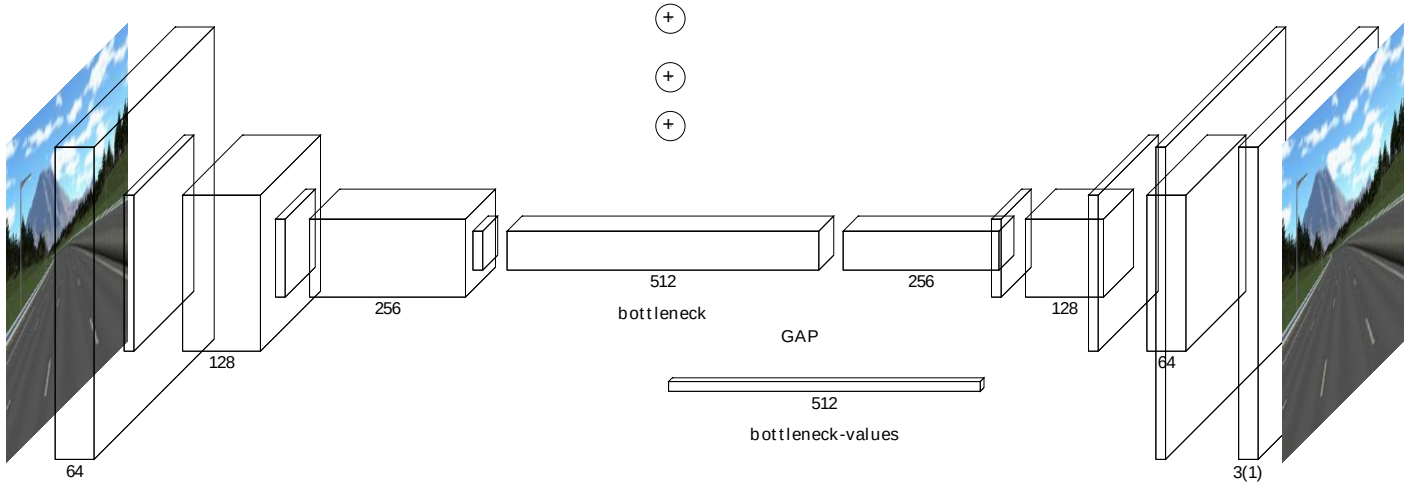
Original

Modified

Greyscale

Experiments Setup (Autoencoder)

- Encoder: 3 (conv + pool) + conv
- Decoder: 3 (deconv + ups) + conv
- Optimizer: Adadelta
- Loss: mean_squared_error
- Epochs: 1000
- Batch size: 10



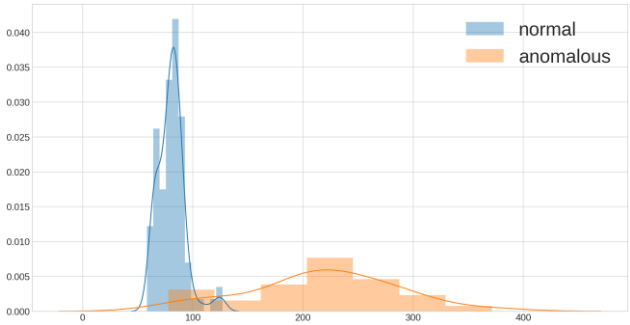
Results (Anomaly Scores Distributions)

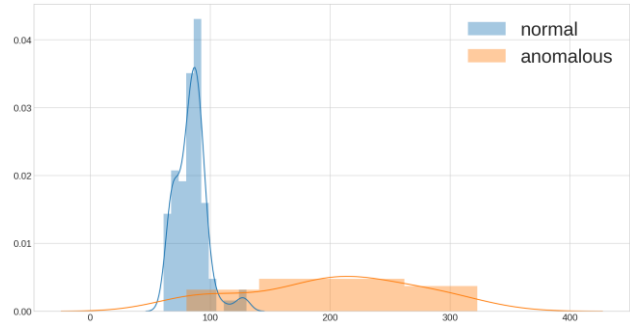
Original images

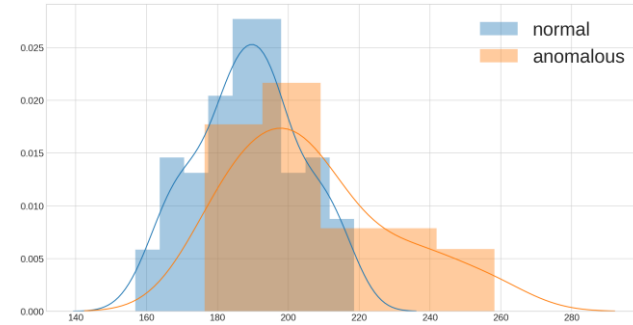
Modified images

Greyscale images

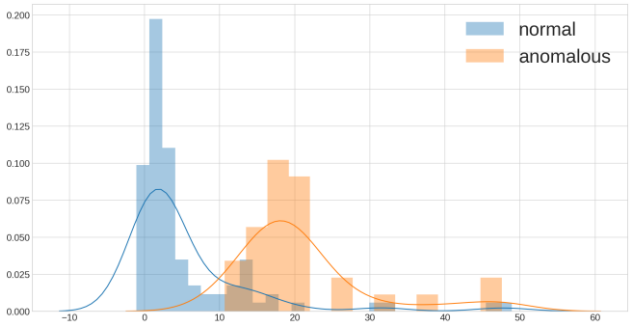
Reconstruction error approach

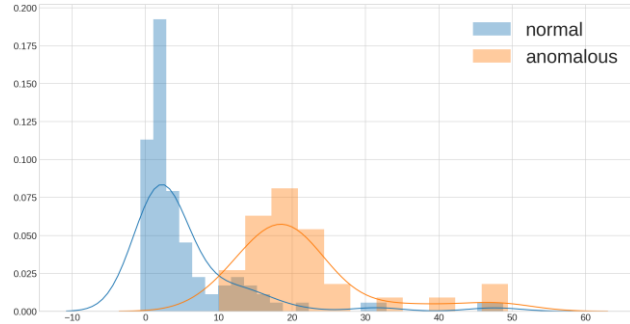


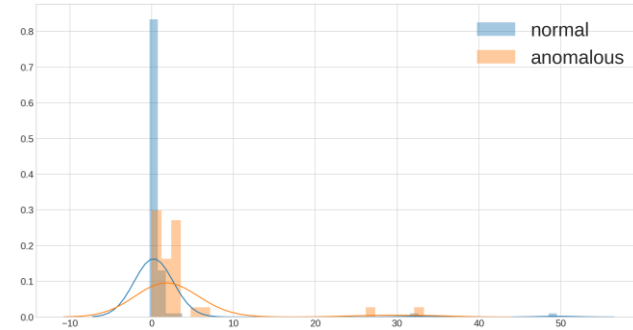




Bottleneck-values approach

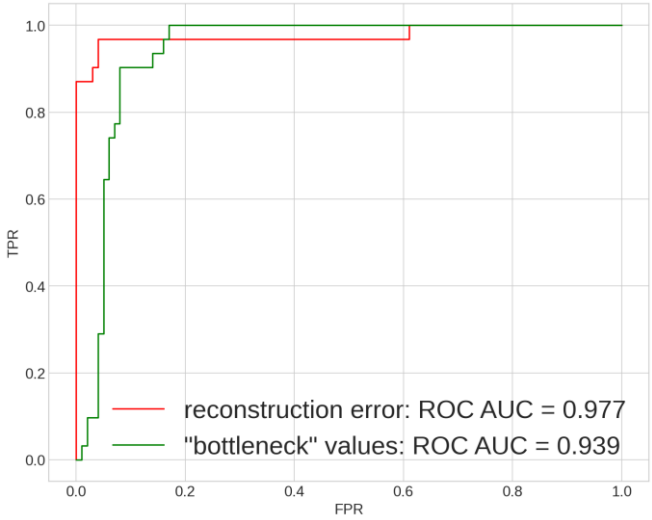




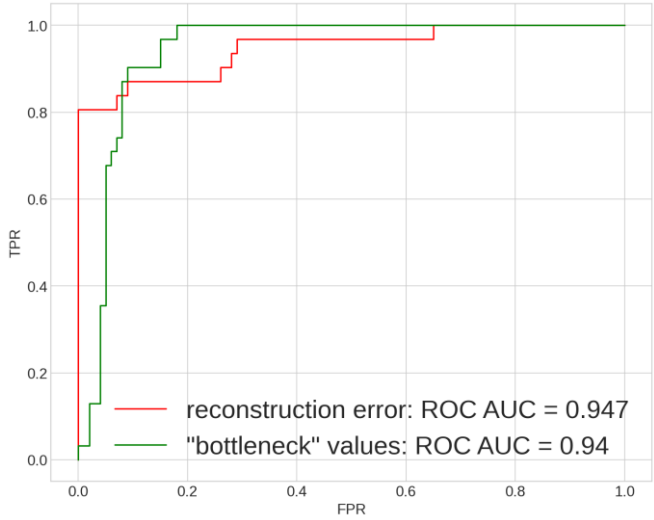


Results (Receiver Operating Characteristic)

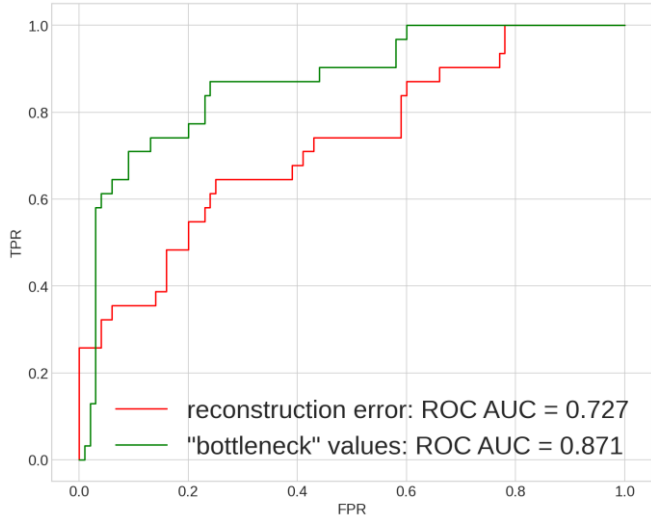
Original images



Modified images



Greyscale images



The performance is better when ROC AUC is close to 1. FPR@100 – false positive rate at 100% true positive rate.

Conclusion

- Reconstruction error approach of autoencoder-based anomaly detection is sensitive to the colors of the anomalous objects (vehicles).
- Bottleneck-values approach of autoencoder-based anomaly detection is not sensitive to the colors of the anomalous objects (vehicles).
- In general, bottleneck-values approach is less sensitive to the color information in images compared to reconstruction error approach.
- Reconstruction error approach has shown high FRP@100 (more than 60% for all cases).
- Bottleneck-values approach has shown lower FPR@100 (less than 20% for original and modified images and less than 60% for greyscale images).
- Future research may include experiments with more complex autoencoders, using real driving scenario images, and considering different types of anomalous objects (e.g. pedestrians, animals, etc.).

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